

# Systemic Analysis Approaches for Air Transportation

**Sheila Conway**

PhD Candidate, Old Dominion University  
Researcher, NASA Langley Research Center  
Hampton, Virginia USA  
[Sheila.R.Conway@NASA.gov](mailto:Sheila.R.Conway@NASA.gov)

## Abstract

Air transportation system designers have had only limited success using traditional operations research and parametric modeling approaches in their analyses of innovations. They need a systemic methodology for modeling of safety-critical infrastructure that is comprehensive, objective, and sufficiently concrete, yet simple enough to be used with reasonable investment. The methodology must also be amenable to quantitative analysis so issues of system safety and stability can be rigorously addressed. However, air transportation has proven itself an extensive, complex system whose behavior is difficult to describe, no less predict.

There is a wide range of system analysis techniques available, but some are more appropriate for certain applications than others. Specifically in the area of complex system analysis, the literature suggests that both agent-based models and network analysis techniques may be useful.

This paper discusses the theoretical basis for each approach in these applications, and explores their historic and potential further use for air transportation analysis.

## Need for Complex System Modeling

**Why Model?** Models are necessarily simplified abstractions of reality for understanding specific properties of a subject. Heylighen (1993) likens models to knowledge itself. As abstractions of reality, he asserts they are vital simplifications and an

“attempt to represent the environment in such a way as to maximally simplify problem-solving.” He continues that a model is not to be judged on its correctness in terms of its ability to yield absolute or complete truth, but rather on its ability to provide insight.

Simply stated, models are our windows to understanding the world around us. Wilson (1998) concurs with this sentiment, saying, “A Model is the explicit interpretation of one’s understanding of a situation, or merely of one’s ideas about that situation. It can be expressed in mathematics, symbols, or words, but it is essentially a description of entities and the relationship between them. It may be prescriptive or illustrative, but above all, it must be useful.” Selecting an appropriate model is then highly dependent on the subject and the addressed concern.

Wilson’s statement raises the issue that modeling itself does not impose a particular implementation, method or tool, but rather is the process of interpretation. All models share the same interpretive goal, but many different types of models, and their associated tools and techniques, may be able to achieve it. Selection should be based on the intended purpose of the model.

**Modeling Systems.** The real world is a big place that can be difficult to understand. To avoid being overwhelmed by its sheer size or complexity, we are inclined to parse it into manageable, and hopefully functional, parts through abstraction. This parsing can be at any granularity (pixilation, or scale), but tradeoffs are made between the size of the parts and the utility of the abstraction: too big, and it is still

unmanageable, too small and it may no longer represent the phenomena of interest. A system is such a parsing. The context in which it is formed must be kept with it.

Kast and Rosenweig (1972) define a system as an organized assemblage of smaller units that form a unitary whole. Others identify the interdependence and complexity that their relationships inherently contribute.

Without models, we can't do much with systems. In fact, Forrester (1987) held the belief that all "systems" are mental constructs of portions of the real world, and that we can't even imagine a system without modeling. Such a bold statement brings to mind a riddle about a tree falling in the woods, but there is no doubt that to understand or influence a system requires a model. Whether a mental model, a mathematical model, or a simulation, Forrester had a point: system models are a basis for action. We have expectations for our systems, and we would like to be able to influence their behavior. However, a system's reaction to intervention is not always clear, nor easy to predict. As systems become more complex, with a greater number of interrelated components, their response to intervention can become even more ambiguous. In fact, as even linear systems become complex in the structure of their interrelationships, their behaviour can begin to appear chaotic.

**Modeling Complex systems.** Modeling complex systems adds some additional limitations and assumptions to the already challenging task of systems modeling. The scientific method and good engineering practice require us to observe, hypothesize, predict, test, derive a conclusion, and repeat until a satisfactory solution is obtained. How is the safety of a new air traffic control technique to be tested without putting aircraft and people at risk? Even if safe, what effect will the new operation have on traffic flow management, or an airline business?

In a complex world, answers to such questions are not always obvious, and can be

counterintuitive. In fact, there are numerous accounts of system changes that had unanticipated and sometimes dramatic results, like the deregulation of the power industry in California (which caused rolling power outages). Often these 'surprises' are results of oversimplification, ignoring system dynamics or even misinterpreting the 'system' itself by not recognizing important elements, or including superfluous, confounding ones.

One obvious issue with complex system modeling is compliance with the principle of Occam's Razor. How to select a model that is simple enough to field, yet captures the nuances of a complex system? Heylighen's statements imply that comprehensiveness is not necessary. On the contrary, he implores us to look for the simplest model that explains observed behavior. As a guiding principle, controlling scope, or the inclusion of detail, will require substantial domain knowledge and explicit recognition of the context. A complex system cannot be trivialized with a simple treatment.

Rather than assume that everything within a system can be equivalently described by a single type of abstraction, matching a model to reality begins with an honest assessment of the fidelity of what is 1) known and 2) what knowledge is desired. This issue of scope for each model element is paramount to successful complex system modeling. One might assume modelers are granted authority to scope as they see fit, but unfortunately, that is not always the case.

Another broad category of issues is expectations: 1) Qualities inherent to complex systems may make understanding analytical results open to interpretation. 2) Complex system analyses may disappoint those who are concerned with output rather than outcomes. 3) Complex systems are often ill structured and changeable. Thus, modeling them can be difficult, costly, and never quite complete compared to more simple systems.

Finally, though important in all systems modeling, being able to gauge a system's robustness becomes imperative with increasing system complexity. Complex system models have limited optimizing ability. The nature of complexity requires models to address fuzziness, non-determinism, and multiple objectives by affording exploration of sensitivities to assumptions and environmental uncertainties.

## **Air Transportation System Analyses**

"The changes that are coming are too big, too fundamental for incremental adaptation... We need to modernize and transform our global transportation system, starting right now." (U.S. Transportation Secretary Norm Minetta, 2004). Ultimately in the case of air transportation, national governments are largely responsible for both setting policy, and implementing infrastructure implied therein. To do so necessitates consideration of both the effectiveness and repercussions of actions within the air transportation system (ATS).

As Wieland et al (2002) point out, modeling the ATS, "with all its interrelated components – mechanics, human decision making, and information flow, is a large effort involving multidisciplinary and 'out-of-the-box' thinking. ...The challenge is not only to represent physical NAS [National Airspace System] dynamics, but also to incorporate the behavioral and relational components of NAS decision making that are an important part of the system. ...A comprehensive model is incomplete and subject to first order errors unless all such interactions are incorporated to some degree."

Wieland et al stress the necessity for ATS modeling at three different time horizons for various purposes: tactical (predictive), strategic planning (investment and policy), and a posteriori analysis (also investment and policy). Their claim is that a useful simulation of the ATS intended for setting policy must model the economic, informational and

mechanical factors of the system and their interactions, or gross errors will occur. They go on to recognize that this is a tall order indeed, and that a comprehensive ATS model is a "grand challenge," albeit necessary and attainable.

Actually, NASA has recognized the need for a more systemic study for some time. They commissioned Krozel (2000) to review all the research related to distributed air traffic management, a widely accepted development concept. He identified not only existing research, but also research needs that were not being met. In summary, he found that at the time, there were no tools capable of assessing both new and traditional ATS operations simultaneously, or their interactions.

Carley (1997) claims "social, organizational and policy analysts have long recognized that groups, organizations, institutions, and the societies in which they are imbedded are complex systems." When it comes down to it, policy analysis is about complex system design in light of uncertainty.

Certainly, complexity and uncertainty will abound in ATS transformation. Influencing ATS performance within itself is complicated enough, but ATS policy reaches outside this arbitrary system boundary. Sheate (1995) complains that standard ATS policy decisions have lead to a business market that decides "where capacity is needed and therefore fails both to maximize the use of existing airport resources and to recognize the importance of environmental capacity constraints." He argues for policy analyses that consider the interplay of system capacity, demand, and aircraft capability.

Unfortunately, policy analysts in the ATS arena have continued to use methods more suited to regularly-behaved systems to develop strategy. Apparently, this is a pervasive problem throughout the policy community. Bankes laments that there are "few good examples of the classical policy analysis tools being successfully used for a

complete policy analysis of a problem where complexity and adaptation are central.” He continues to say that policy analysis in the face of “deep uncertainty” must focus on robustness rather than single-point optimization. This reinforces the notion of developing many different plausible environmental scenarios, and recommending policy that is viable across their range. Addressing this same concern, Iyer (2000) offered that the “basic contribution of complexity theory [to planning] is its focus on systemic interactions at various scales...” that can address uncertainty.

Moss expresses the view that “Policy analysis has to start with observation and the specification of a problem to be solved.” From there, appropriate analysis tools can be defined. Moss, Iyer, and others suggest that deterministic and even stochastic approaches to complex policy development are incompatible, though agent-based modeling (ABM) may be workable.

Though the ATS research community has attempted to model particular attributes of the system, there hasn’t yet been a method capable of answering questions regarding the systemic response to substantive changes in operations. To date, agent-based, elemental simulations have proven too expensive and unwieldy to complete. Parametric simulations have failed to provide the flexibility to be used as design tools.

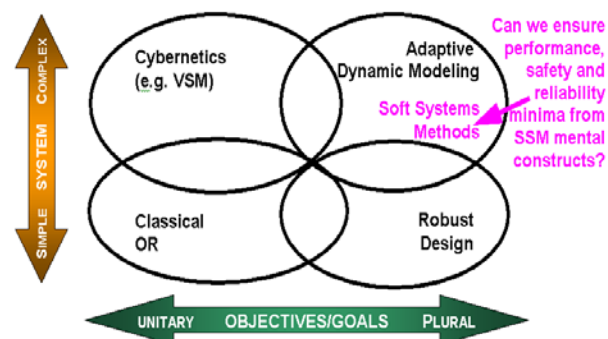
The dearth of appropriate analytical tools is not due to a lack of demand, or trying. It has simply proven to be very difficult. Calls for systemic simulation for operational design of the ATS continue to accrue, from the responsible government officials, to the researchers in the trenches.

### A (Discretized) Continuum of Potential Modeling Approaches

Just as systems themselves differ in objectives and complexity, so do the models

that describe them. Regardless of the approach used, Andrews (2000) implores modelers to not loose touch with purpose of their effort, and to build models that “appropriately and credibly” simplify reality within specific context of the system at hand.

Within the literature, there is consensus that: 1) Systems modeling is a useful a way of solving real world problems, particularly when prototyping or experimenting with the real system is expensive or impossible. 2) Different types of applications call for different modeling techniques (figure 1).



**Figure 1. Methods and application within problem context (adapted from Daniel)**

Many different modeling approaches have been offered in the literature. Generally speaking, these different approaches are intended to address specific classes of systems. A model’s capabilities have to match the system’s overall attributes. Many authors summarize these attributes in system classifications, which, of course, vary within the body of work. Authors find their own dimensions on which to split the space of possible systems. In the realm of complex systems, which nearly all classification schemes include, authors have deemed most modeling approaches *unsatisfactory*, leaving precious few potential choices for those interested in complex system modeling.

Daniel (1990) described the possible space of systems in two dimensions, along the attributes of complexity and the number of objectives a system operates to control. He suggests that classic Operations Research

(OR) modeling techniques are best applied when the system can be described in great detail and a single optimization function is the primary focus of study. He reports the static nature of OR models is an inherent limitation. Not only does OR require detailed system knowledge, the system is implicitly expected to remain unchanged.

He offered cybernetics as an approach that acknowledges the importance of both system structure and the interaction of components that can cause dynamic behaviors. However, he implies its limitations lie in the singularity of its optimization goals. Others have enumerated additional challenges with cybernetic deployment.

Daniel continues that of the many systems modeling techniques described in the literature, soft systems methods (SSM) are particularly well suited to complex systems: Complex systems are represented in the upper right of his systems space. They are context-rich, non-linear problems that cannot be expressed by a single set of objectives or goals. SSM involve the development of a rich picture of the problem, putting great emphasis on framing the problem correctly within context. However, these methods have been criticized for being unverifiable, non-quantifiable, and lacking in rigor (Lane 1998).

Additionally, if effecting systemic improvement is a modeler's goal, the ability of the output/outcome to be influential has to be considered. For a safety-critical system with minimum performance criteria, mental constructs (and the flexibility they provide as "controlling" qualities as in SSM) have not proven influential in many circles. Many systems, air transport included, demand rigorous evaluation before change is even considered.

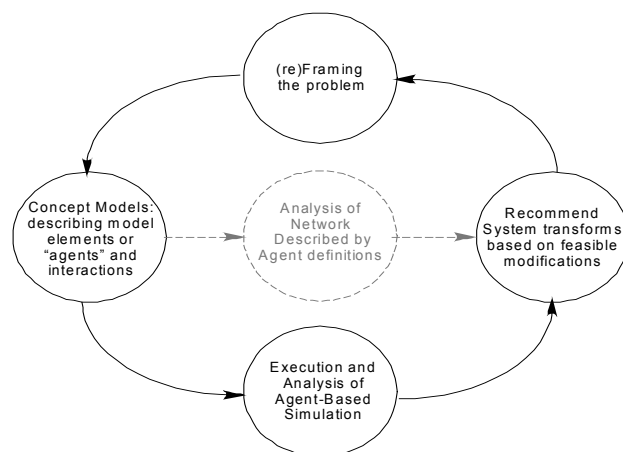
Sterman (2002) warns that SSM often leads to "wildly erroneous inferences about system behavior", dramatic underestimation of the dynamics of systems, and incorrect conclusions. In fact, Moss (2002) goes so far

as to say that soft approaches as well as traditional, "harder" ones will *never* support effective policy analysis. How then to address complex systems in both a rigorous but sufficiently realistic and tractable way? Moss provides a suggestion, saying; "adaptive agent modeling [e.g. ABM] is an effective substitute" for other analyses in the complex system realm.

Borshev and Filippov (2004) interpret the potential systems modeling space differently than Daniel. Borshev and Filippov's orthogonal dimension to complexity is discreteness, that is, the level of abstraction or aggregation in model elements. Interestingly, they also make a distinction between system types that necessitate simulation vs. those better served by analytical models. They prefer analytical solutions when a closed form solution is obtainable. Thus, they imply one ought at least to consider such a model first, because simulation, they argue, is not trivial. However, they continue by saying that "for complex problems where time dynamics is important, simulation modeling is a better answer," narrowing the field of potential modeling techniques.

Akin to Andrews, Borshev and Filippov suggest matching modeling techniques to the "nature of the problem," and that any one technique will almost surely not be most appropriate for all systems. Rather they call for modeling techniques that "would allow for integration and efficient cooperation between different modeling paradigms." They discount other complex system simulation options, but conclude that there is a place for both system dynamics (SD) and ABM. They found ABM well suited to systems where most knowledge is at the local level (e.g. agent-level) and little or nothing is known about global interdependencies. They also concluded that SD could be more efficient, particularly if agents are uniform and/or have little true "active" or autonomous behavior, and discuss the use of both techniques in combination.

While full-scale agent models can be as complex and costly to develop as a large-scale parametric model, there may be a means of validating models and educating a number of higher-order effects without constructing and running full-scale agent-based simulations. From the description above, it is clear that interaction among agents could be described by network structure: there are well-defined nodes (agents) and links (interfaces, interaction protocols). Network analysis (NA), developed in the field of network theory, could be applied to a network defined by the agents' communications demands. These may provide a relatively simple and reliable means of evaluating the aggregate performance of a complex system, similar to SD, with less effort than an ABM (Figure 2).



**Figure 2. ABM and NA Relationship**

By using dynamic or adaptive modelling methods when dealing with complex systems, the possible modeling space is reduced dramatically. The three methods identified in the literature as applicable for capturing dynamic behavior are worthy of further consideration:

**System Dynamics (SD).** Forrester, the father of SD, describes system dynamics as the discipline of interpreting real life systems as simulation models. These models highlight the structure and decision-making processes within a system that give rise to its behavior. As the name implies, SD is the study of the interactions of system elements via feedback

and feedforward loops causing attenuation and amplification of system attributes respectively. Often the metaphor of stocks and flows is used to illustrate the approach. SD models are time-dependent linked mathematical models exploiting differential calculus.

Borshev and Filippov note that SD is similar in nature to dynamic systems, or simply “dynamics,” taught in technical engineering disciplines, but uses language and notation more familiar to systems analysts. As with dynamics, rigorous treatment, unavailable with cybernetic models equivalents, is possible. They comment that dynamics are taught to mechanical, aero and electrical engineers “as a standard part of the design process.” These members of the academic community acknowledge the necessity for systemic dynamic analysis for design, at least for physical systems.

Unfortunately, SD requires extensive system knowledge a priori, including all system elements and potential communications between them. This makes building a comprehensive model of a complex system an enormous effort. Systems that change frequently or have a high degree of uncertainty may not be amenable to SD at all.

Despite this major drawback, many authors have used SD to model complex systems. In its favor, analysis and control techniques for the resultant mathematical models are well established and have proven to be highly serviceable.

**Agent-Based Modeling (ABM).** Agent-based modeling (ABM) techniques have been proposed as an alternative to traditional parametric models because they can exhibit higher-order behaviors based on a relatively simple rule set. ABM uses agents to execute model functions. They are the active components of an agent-based simulation.

Agents are ‘autonomous’ in that they have interfaces to the general simulation, but carry within them their own ability to perform their assigned tasks without a centralized controller.

Agents are interactive entities that capture salient but generally localized behavior of system elements. Using simple rules to determine each agent's actions, higher-order systemic behaviors can emerge. Jennings (2000) offers further detail, saying agents:

- 1) have defined boundaries & interfaces.
- 2) are situated in a particular environment.
- 3) strive for specific objectives.
- 4) are both reactive and proactive, and
- 5) are autonomous (distinct from objects).

Jennings would most likely agree that ABM is not well suited to all systems. However, he outlines his argument in favor of ABM of complex systems, saying complex system development requirements and ABM are highly compatible. He argues that ABM is particularly well suited to complex systems because it:

- 1) partitions a complex problem space.
- 2) naturally abstracts complex systems, and
- 3) captures dependencies and interactions.

However, he also admits that these same properties can lead to issues of unpredictability and apparent chaotic behavior. Unpredictability is a problem in the simulation world because it makes internal validation very difficult when exact results cannot be repeated. The lack of deterministic behavior is also a problem for validation. Jennings and others claim that these difficulties can be circumvented by formally analyzed interaction protocols, limiting the nature of agent interaction, and adopting rigid organizational structure among the agents.

Much hope is laid at the feet of ABM, particularly in the social science realm where complexity and uncertainty are paramount. From recent literature, Bankes (2002) summarizes three reasons why ABM is potentially important: 1) the unsuitability of competing modeling formalisms to address the problems of social science, (2) the ability to use agents as a natural ontology for many social problems, and (3) the ability to capture emergent behavior.

While the latter two arguments are similar to those of Jennings, Bankes claims dissatisfaction with the restrictions imposed by alternative modeling formalisms is driving modelers to agent-based solutions. In his opinion, the most widely used alternatives, systems of differential equations and statistical modeling, are viewed as imposing restrictive or unrealistic assumptions that limit many applications. He says "The list of assumptions that have been objected to is lengthy, but it includes linearity, homogeneity, normality, and stationarity."

What Bankes fails to mention is that these shortcomings are not necessarily avoided just by deploying ABM approaches, and certainly not by agent implementations of standard methods. A model still has to be appropriately defined to describe significant features for the system served. Additionally, addressing issues such as homogeneity requires not only more effort in model specificity, but also more information related to distributions of variables or behaviors. These data may not be available. A homogeneous population model might be of sufficient fidelity for describing some systems, while an assumed (but erroneous) normal distribution, for example, might yield misleading results. A more complex or detailed model (e.g. at the agent rather than the aggregate level) is not necessarily more accurate.

Arthur (1994) suggests agents are a natural way to deal with ill-defined or complicated "reasoning" within a system, oft induced by inclusion of humans. He argues, "beyond a certain level of complexity, human logical capacity ceases to cope – human rationality is bounded." Agents can be designed to mimic the inductive behavior of people when placed in unfamiliar or complicated environments. However, the example he provides, a problem of deciding whether or not to frequent a bar based on the expected crowd, exemplifies a prime concern with assuming agent "intelligence" (which has to be present to

differentiate the agent from a mere object in Jennings terms). In his example, the agents select from a pre-determined set of schemata based on some outcome metric (actual number of bar patrons). Can this be considered true inductive behavior? The “induction” was accomplished [by the modeler] in the generation of the options, not by the agent in their selection later on.

If appropriate strategies were not included in the agent’s definition, Arthur’s agents would have never succeeded. Recognizing this, he does acknowledge that people’s inductive ability [emulated by agents using lists, genetic algorithms, etc.] is a “deep question in psychology” and thus can only be marginally imitated. Generally speaking, agent “intelligence” at best will be limited by the degrees of freedom their internal models are allowed to explore, and may be further limited by the methods of exploration.

Bonabeau (2002) claims that ABM is “by its very nature the canonical approach to modeling emergent phenomena” of complex systems, necessary for analysis of non-linear behaviors, localized phenomena, and heterogeneous populations. However, like Jennings, he acknowledges difficulties in building agent models of large systems because of the myriad low-level details and the “extremely computation intensive and therefore time consuming” model that results.

**Network Models.** Network theory is an extension of graph theory. By definition, nodes that constitute a network are interconnected in some way or another by links. The resultant network can be categorized by its structure. In turn, this structure imparts peculiar characteristics to both the system as a whole and to the individual nodes. Following specific connectivity rules, some networks have some nodes that are highly connected while others have only a few connections. In other networks, links are randomly formed but still obey statistically generalizable patterns.

All networks can be analyzed by some basic, quantifiable measures including their degree distribution and their average clustering coefficient (Wuchty et al, 2003). Stemming from these basic metrics, networks often exhibit higher-order dynamic functions, thought to be associated with their unique structures. These include robustness, fragility, percolation and searchability.

The ability of NA to differentiate operationally unique airline route strategies and their resultant distinctive structures is yet to be shown. Due to the relatively small number of nodes in air traffic networks, nodal separation distance and searchability tend to be straightforward to determine and not too instructive. However, because of the criticality of the application, resilience to cascading failure, percolation, and congestion robustness are of utmost interest in the ATS. It is not clear if NA will be able to reveal these qualities sufficiently. Braha and Bar-Yam (2004) suggest that the approach is worthy of pursuit, as functional classes of networks might be expected to have differences in their topologies, such as directedness. These in turn could be expected to lead to particular dynamic potentials.

Latora and Marchiori (2001) call for the measurement of average path length, clustering coefficient, average degree, and degree distribution as do Strogatz, Watts, and others, but also suggest the use of efficiency and cost. They define efficiency at both the local and global level as “the measure of how efficiently it [the network] exchanges information.” They suggest that efficiency is really a more general measure for path length and clustering, useful because other measures can only be defined for certain network subclasses. Efficiency can be applied to any network, but it can be difficult to calculate.

Latora and Marchiori argue that the Watts/Strogatz measures are only effective in quantifying a network in the “topological abstraction, where the only information



retained is about the existence or absence of a link.” Following the above arguments that quality/cost of the links are paramount to describing operational functionality, it appears unlikely then that topological metrics alone will be useful abstractions for describing air transport networks. Using the Boston Subway as an example, they suggest that substituting efficiency measurements resolves difficulties in general application of network topologic analyses to weighted and directed systems.

Once measured, Latora and Marchiori show that efficiency metrics can be used as indicators of potential cascading failure, and can be used as a “measure of performance” of the network. They showed marked differences in the non-linear behavior (onset of cascading failure) of two different, well-documented network topologies.

**Multimethod Approaches.** The use of more than one method in a single modeling effort may be the most promising approach to complex system analysis. Multimethodology may enable modeling of inhomogeneous elements of a complex system, each element matched to an appropriate modeling method. This strategy may be important where a lack of complete system knowledge inhibits the use of a single model type. It might also be useful when the scope of the system represented in a single scale would cause the model to become too cumbersome. Multiple methods could be applied in successive phases of an effort, or in parallel, representing different levels of fidelity for various subsystem models.

Mingers (2000) proclaims, "Multimethod is not the name of a single method, or a specific way of combining methods. Rather it refers in general to utilizing a plurality of methods or techniques, both quantitative and qualitative, within a real-world intervention." Declaring multimethodology as a distinct analytical approach or even as “new” may be a disservice to best practices within systems science. Perhaps multimethodology is more a matter of emphasis than a totally new

paradigm. For example, a good modeler would be hard pressed to generate any “hard” model (e.g. ABM or SD) without some effort to capture significant system context or a clear understanding of the problem at hand. Using SSM adds formalism to this step that in turn may improve the product.

What Mingers and others offer is balance to the process. Their claim, based on a number of examples, is that modelers will tend to focus on the data at hand, and not on modeling the primary driving functions of a system. Models tend to be concentrated on directly measurable quantities, and ignore or de-emphasize less well-behaved system components (such as people). Freeing the modeler to use all available and suitable techniques rather than a single model for the entire system should produce a better, more tractable product with less effort.

Regardless of the declaration of multimethodology or not, the concept is well established in practice.

## Summary

The majority of ATS researchers have joined Wieland et al. in suggesting that specific classes of tools represented by ABM and/or network analysis are perhaps the only modeling solutions currently available that offer systemic utility. Holmes and Scott (2004) say, “Proposed ideas for changing the NAS should not be contemplated lightly, due to the sheer size and complexity of the system. Instead it will require a fundamental reconsideration of how such complex systems are analyzed and designed if the system to evolve remains productive and viable. Traditional methods for analyzing changes to complex systems fail when applied to highly dynamic and interconnected system such as the Internet or the NAS.” They outline a case for using agents operating on networks as a viable analytical alternative.

The literature suggests that both NA and ABM are well suited to study emergent,

complex behavior within the context of air transportation. From the outset, differences in both scope of effort to establish these two models and expectations for their results should be acknowledged. NA is focused at systemic-level solutions, much like system dynamics, while ABM revolves around the “unit” of the system. Is the additional information (at the agent level) necessary or even useful for a transport system study? Is the system so sensitive to assumptions of individual behaviors that ABM predictions are no better, or in fact worse, than more generalized network analyses? On the other hand, are NA so aggregated that system dynamics are poorly described?

Either approach, or perhaps both in combination as Mingers might suggest, may provide clues for uncovering problems, provide confidence about systemic performance, and contribute to developing mitigation strategies for systemic ATS issues.

## References

- Andrews, “Restoring Legitimacy to the Systems Approach” *IEEE Tech & Society Mag*, v. 19 n.4, p.38-44, winter 2000/2001.
- Arthur (1994), “Complexity in Economic Theory” *Amer Econ Revw*, v.84, n.4, p.406
- Bankes(2002) “Agent based modeling: Revolution?” *PNAS*, v99 n3 p7199-7200
- Bonabeau (2002) “ABM: Mthds & technqs for sim human sys”, *PNAS* 99/3 p 7280-7287
- Borshchev & Filippov (2004) “From Systems Dynamics and Discrete Event to Practical ABM”, *Sys Dymcs Soc Conf*, Oxford, UK
- Braha and Bar-Yam (2004), “The Topology of Large-Scale Engineering Problem-Solving Networks”, *Physical ReviewE*, v.69
- Carley (1997) “Extracting team mental models thru textual analysis” *Jrl Org Bhvr*, 18, p533
- Forrester, J. “Fourteen ‘Obvious Truths’” *Sys Dynamics Revw*, v.3 n.2 p.156-159. 1987
- Heylighen (1993): “Epistemology”, *Principia Cybernetica*, URL: //pespmc1.vub.ac.be
- Holmes and Scott (2004), “Trnsprtn Ntwk Tpolgies”, 4<sup>th</sup> Intg CNS Conf, Fairfax, VA
- Iyer (2000) “Can Complexity Theory Enter the World of Planning” *Critl Planning*, v7 p25
- Jennings, (2000) “On Agent-based software engineering” *Artfcl Intlgnce* 117, 277-296
- Kast & Rosenweig (1972) “General systems theory” *Acad Mgmt Jrnl*, v.4 p. 47
- Krozel, (2000) “Free Flight Research Issues and Lit. Search”, NASA, NAS2-980005
- Lane and Oliva, “The greater whole: towards a synthesis of SD and SSM” *Euro Jrnl of Opra’l Rsrch*, v. 107 n.1 p.214-235, 1998.
- Latora & Marchiori(2001) “Efficient Behavior of Small-World Networks”, *Physl Rvw Lters*, Amer. Physical Society, v.87 n.19
- Mingers (2000), “Variety is the spice of life: Combining soft and hard OR/MS” *Intern’l Transactions in OR* 7, 6, pp. 673-691
- Moss (2002) “Policy analysis from first principles”, *PNAS* v.99 sup.3, p.7267
- Sheate, “Transport policy: a critical role for strategic environmental assessment” *World Trnsprt Policy and Prctice*, v1 n4, p.17, 1995
- Sterman, “All models are wrong” *Systems Dynamics Review*, v. 18 n. 4 2002
- U.S. Transportation Secretary Minetta, speech to Aero Club of Wash DC, Jan 27, 2004
- Wieland, Wanke, Niedringhaus and Wojcik, “Modeling the NAS: A grand challenge for the simulation community” *Soc. for Computer Sim*, San Antonio, TX, 1/2002
- Wilson, E. (1998) *Consilience: The unity of knowledge*. Knopf, New York, NY
- Wuchty, Ravasz and Barabasi (2003) “The Architecture of Biological Networks”, *Complex Systems Science in Biomedicine*, Kluwer Academic, New York

## Biography

Sheila Conway is a researcher at NASA Langley Research Center in Hampton, Virginia and a Doctoral Candidate at Old Dominion University. Her experience includes engineering design and systems development. She is a commercial pilot and an instrument flight instructor.